Application of Machine Learning Techniques in Phased Array Antenna Synthesis: A Comprehensive Mini Review

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***Abstract*—With the rapid development of modern communication systems, phased array antennas (PAAs) are widely used in many applications such as radars and 5G networks. In a PAA composed of multiple elements (antennas), beamforming or beam steering can be achieved by adjusting the phase difference in the excitation signals that feed each element of the array, eliminating the need for mechanical antenna movement. The performance quality of the communication systems heavily relies on the precise synthesis of the PAAs. PAA synthesis entails determining the geometric or physical shape of an antenna based on knowledge of its electrical parameters. Conventional methods for PAA synthesis use conventional electromagnetic models embedded in antenna design software's. However, these models often pose challenges due to resource-intensive computations, lengthy simulation times, and potential high error rates. Machine learning (ML) techniques can be employed to optimize solutions in various telecommunication systems, including PAAs synthesis. In this article, we review and investigate the application of ML techniques in the synthesis of PAAs. The results of this study show that utilizing ML techniques can expedite the design process by threefold, while simultaneously reducing errors and increasing accuracy up to 99%.**

***Keywords*—phased array antenna, machine learning, deep learning, artificial neural networks**

I. Introduction

Today, artificial intelligence (AI) techniques are extensively utilized in communication systems, both in the physical and upper layers, which include detection and decoding, wireless communication networks, cellular networks, cognitive radio, wireless sensor networks, cyber security, and the design of various types of telecommunication antennas. Machine learning (ML) has demonstrated remarkable advancements in antenna design for a wide range of telecommunication systems, including millimeter wave systems, body-centered telecommunication systems, THz telecommunication systems, satellite telecommunication systems, telecommunication systems of unmanned aerial vehicles (UAVs), telecommunication systems of base stations [1], satellite systems [2], and 5G networks [3]. ML employs various techniques to discover optimal geometric structures and patterns from high-dimensional random data in order to design antennas [4], design phased arrays [5], and artificial electromagnetic media such as metamaterials, meta surfaces, electromagnetic bandgap structures, and provide selectable frequency levels [6].

Generally, an antenna can be represented through a mathematical model, as depicted in Fig. 1. The inputs to this system are denoted as x and p, which correspond to the excitation current of the antenna and a set of parameters that define the geometric and electromagnetic properties of the array, respectively. The output (y) is the antenna radiation pattern. It is assumed that x, p, and y belong to either Banach or Hilbert domains. The system is represented by an operator S which is continuous (frequency dependent), and linear in x, but usually not linear in p.

The phased array antenna (PAA) is among the most commonly used types of antennas in telecommunication systems, garnering significant interest from researchers due to its versatile applications. A PAA is a computer-controlled antenna array that produces a beam of radio waves that can be electrically steered in different directions without the need for mechanical movement of the antenna [2].

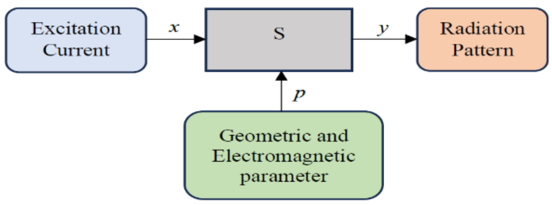

Figure 1. Antenna system mathematical model.

In practice, the optimal radiation pattern for a PAA is formed based on the distributed and independent dynamic control of the phases of PAA elements. Obtaining the

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desired set of excitations of elements (phases of PAA elements) is an optimization problem that is created in conventional optimization methods according to the adopted metric (objective performance). Unfortunately, in conventional optimization methods, it may take a long time to reach an optimal or suboptimal solution. This is due to the inherent iterative nature of these methods and usually requires a large number of iterations or complex calculations to converge.

Conventional optimizations may take a long time to converge to an optimal or suboptimal solution due to their inherent iterative nature, as they usually require a large number of iterations to converge or involve complex computations. Consequently, these methods are not suitable for implementation within a near-term schedule. Furthermore, defect detection in PAA and inverse scattering-based nonlinear problems require complex yet cost-effective solutions, where ML can provide an edge over other techniques. Failure of the elements in a PAA causes drastic field changes in the array apertures, thus the antenna radiation pattern is degrading. ML techniques have previously been used to determine the location of fault element in the antenna array. In summary, several advantages of ML algorithms are highlighted by comparing them with conventional PAA synthesis methods. The main effects include speeding up the design process, reducing errors and time spent, improving the accuracy of antenna design, helping researchers save a lot of simulation work, and suggesting approximate solutions for specific optimization problems. In addition, one of the significant advantages of ML is that ML methods can be learned from data without any prior knowledge and the learned model can be used for future designs.

The synthesis of the radiation pattern of an array antenna is a crucial aspect in the design and implementation of a Phased Array Antenna (PAA). Proper weighting of the array elements plays a significant role in achieving the desired radiation pattern. Array radiation pattern synthesis is widely used to direct energy in specific directions, eliminate sources of interference, or even reduce the likelihood of interference with other systems. Conventionally, filter design techniques are used in radiation pattern combination algorithms for arrays due to the similarity between spatial signal processing and signal amplitude. However, these algorithms often lack the flexibility to consider all constraints Optimization techniques can be a more general solution to produce desirable radiation patterns, despite stricter conditions and more limitations. While the algorithms based on optimization are highly flexible, they may require a substantial amount of time to converge to the optimal solution, especially for large arrays. For fixed or pre-configured radiation patterns, additional computations are not considered a hassle. However, in dynamic scenarios, generating a specific radiation pattern in real-time becomes more challenging.

In contrast to conventional optimization methods in PAA pattern synthesis, ML networks using training datasets that utilize training datasets can achieve faster computational performance compared to conventional optimization methods. Considering the crowded radio spectrum, which requires systems with the ability to reconfigure and adapt to the environment, ML algorithms are widely used in adjustable and adaptive PAAs. To change the polarization in a tunable array, the radiation pattern, operating frequency, and current distribution across the antenna are changed. Adaptive arrays instantly weight and combine signals to obtain the desired pattern and remove interfering signals [7]. In this method, by adjusting the weight of the PAA elements, the antenna pattern is changed. In the conventional mode, pattern forming software algorithms are used to create array patterns. This is where the role of AI in PAA design becomes apparent.

ML algorithms can adjust the weighting of array elements using fast and superior methods. ML can perform better than conventional algorithms in signal processing in noisy and multi-path fading environments. The use of ML according to the antenna array architecture controls the signals with digital beamforming methods. When using ML in the antenna design of telecommunication systems, regression-based algorithms are an essential tool. By using these algorithms and sufficient data sets, a model can be obtained that represents the mapping diagram of the nonlinear relation between the antenna's geometric characteristics and parameters.

One of the most used ML algorithms for designing antennas are artificial neural network (ANN) and support vector regression (SVR) [8]. Other less commonly used regression methods include linear regression (LR), least absolute shrinkage and selection operator (LASSO), Gaussian process regression (GPR), and kriging regression (KR). ML techniques can make the design process three times faster in addition to reducing errors and increasing accuracy up to 99% [8]. ANN algorithms have been used to find relationships between antenna parameters.

In recent studies, many works have been conducted on the use of techniques based on AI and ML to solve problems related to the design of PAAs. In [9], a deep neural network (DNN) was used to perform fault analysis on active phased arrays of 5G and 6G radios. DNN is designed to classify various errors by extracting hidden features in the phase and square components of baseband signals. This method achieves 99% accuracy in detecting the failure of an array element and 80% accuracy in detecting multi-element error. In [10], an effective ML-assisted array synthesis method was presented based on active basis element modeling. In particular, the proposed model considers the mutual coupling effects between each antenna element and the surrounding environment. The result of this study shows that ML-assisted array synthesis method can provide design freedom, improve array performance, enhance design efficiency, and collaborate with different optimization methods. Zhang *et al.* [11] presented a deep deterministic gradient algorithm, which is a typical reinforcement-learning algorithm that has robust fitting ability for high-dimensional continuous nonlinear problems, for pattern synthesis of a phased array antenna. Oliveri *et al.* [12] was placed on the application of ML to speed up the analysis of reflective arrays by

Zhang *et al.* [13] a cognitive antenna array associated with a deep reinforcement-learning model was proposed for fast adaptation to complex electromagnetic environment. This platform includes a vector network analyzer and a micro-programmed control unit to view and adjust the antenna array. The vector network analyzer feeds the signal to the phased array antenna through a power divider and transmits the measured gain to the host computer to invoke the deep reinforcement-learning algorithm, in which case the microprogrammed control unit uses digital phase shifters for each controls the phase shift. The antenna element receives the phase distribution adjustment command from the deep reinforcement-learning model. The result shows a good agreement between the simulated and measured radiation patterns. This algorithm is also used in the design of a coherent PAA, demonstrating the potential for automatic adjustment of different beam angles. With the increasing complexity of the antenna structure, the number of its geometric parameters also increases, making it more challenging to establish relationships between the parameters, the resonance frequencies, and other features of the antenna radiation pattern. The conventional approach to optimize the antenna design is using simulation models for achieving desired pattern. This process is a heavy computation and time-consuming process. Instead of using this method, the antenna design process can be accelerated by utilizing ML techniques, which involve establishing a mapping between the inputs and outputs [14]. In general, antenna design by ML involves four steps, as shown in Fig. 2. Although using ML for antenna design requires simulations to the necessary training data, once trained, it can be used to predict the antenna parameters for any arbitrary input at a higher speed and a lower error compared to the simulation results. In this paper, we investigate the use of ML techniques in the PAA optimization.

The continuation of the paper is organized as follows. In Section II, the literature review will be presented, and in Section III, PAA is described briefly. In Section IV, we review a summary of ML techniques, and finally, in Section V, we will conclude the article.

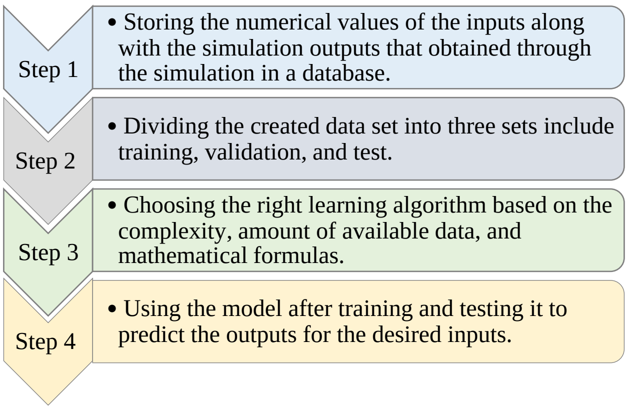


Figure 2. Steps of applying ML for antenna design.

II. Research Literature

The radiation pattern of an array antenna is formed by the amplitude and phase of the signal applied to each of its elements [15]. However, it should be noted that when feeding the array elements, there are many couplings between the elements that are placed together with a distance of less than half the wavelength of the operating frequency. As mentioned, the radiation pattern of an array antenna without coupling can be obtained simply by multiplying the radiation pattern of one element of the array antenna by the *AF*. However, in the case where there is coupling between array elements, it will be difficult to determine the amplitude and phase of the signal for each array element in order to achieve the desired radiation pattern. As a common approach, Fourier transform or optimization techniques can be used to obtain the desired radiation pattern in the array antenna [16–18].

However, these methods cannot be easily implemented in practice. Synthesis of the radiation pattern of an array requires considerable computational time. Simulation of radiation patterns in the design of antennas can be done with simulation software. In this case, to observe the radiation pattern with coupling, it is possible to simulate the radiation pattern by directly introducing a signal with a certain phase difference to each element of the antenna. The presence of coupling causes the radiation pattern to be affected. Therefore, it is essential to find the proper amplitude and phase for the signal applied to the array elements to obtain a radiation pattern without coupling effects.

Recently, ML techniques have been used for the design and synthesis of antennas [19, 20]. ML can be used to determine the amplitude and phase of the signal required to synthesize the radiation pattern of the PAA when coupling is considered. Distortion of the radiation pattern due to the existence of coupling between the elements of the antenna array is intensified by decreasing the distance between the elements of the antenna. To minimize side effects caused by coupling between array elements, neural network-based methods for radiation pattern synthesis have been studied [19, 21]. The radiation pattern is mainly determined by the phase of the signal that excites the antenna element. Different radiation patterns are obtained for different signal phases. The relative phase difference is more important than the absolute value of the phase. Therefore, the phase of the first element in the array is kept constant at zero degree and the phase of the other elements of the array is compared with it.

When using ML techniques, the radiation pattern of the training data can be obtained by increasing the phase to a certain extent. In this way, every time the phase value increases, a certain number of states will be created for the array elements. Therefore, a number of radiation patterns corresponding to these states will be produced. To verify whether the DNN is properly trained, the validation data must not overlap with the training data. Determining the type of input and output of a DNN is very important because the learning results can be completely dependent on the type of input and output data. The total number of radiation patterns will be proportional to the number of array elements and the number of phase difference angles considered for array elements. In simulator software, amplitude and phase of signals are known as variables. The desired antenna patterns are simulated and stored using a computing and simulation software. The antenna amplitude and phase variables are entered into the simulator software and the radiation pattern is extracted. As the depth of the neural network increases (the number of hidden layers of the neural network), the number of output neurons decreases.

For training, a certain number of radiation patterns generated by the software simulators are used). The training execution time in the neural network algorithm is reduced by using appropriate hardware. By substituting DL techniques instead of electromagnetic simulation in addition to reducing the computation time, the error is also reduced [22, 23]. Moreover, when some elements of the array fail, the radiation pattern of the array also changes, and in this case, a NN can be used to detect the failed elements of the array [24].

In addition, the NN can be used to determine the excitation signal of the array elements [25, 26]. The study of antenna pattern synthesis based on NN has revealed the feasibility of DNN as a logical candidate for learning desired radiation patterns. So, a DL-based method for estimating the excitation signal of array elements by interpreting the desired radiation pattern is also suggested.

A. Related Works

Although the topic of this article is about the application of ML in PAA synthesis, some other applications of ML in PAA such as fault diagnosis and beamforming also are presented in this section.

1) Application of ML in PAA synthesis

Various studies have been conducted in the field of using ML in the design and optimization of PAAs. In this section, we have an overview of some of the researches that have been done in this field in recent years. Shan *et al*. [25] the possibility of applying DL techniques for the synthesis of reflective arrays is investigated. In this paper, a deep CNN is proposed to predict the phase shift in a reflect array antenna. The proposed network receives the radiation pattern and the direction of the pattern along with the training data and the test data obtained by the array theory as input to the model. After sufficient training, the proposed network has strong approximation ability and correctly predicts the phase change. The results of the paper show that deep CNN can mimic the phase synthesis process of reflect arrays and have great potential for continuous phase prediction in more complex array synthesis problems. As mentioned above, array synthesis means calculation of phase values of the array elements for obtaining desired radiation pattern for array. Lovato and Gong [26] a CNN is designed and trained to synthesize an 8×8 planar PAA. In this architecture, a desired two-dimensional radiation pattern is processed to calculate phase values for PAA synthesis .The performance of the network is evaluated using data that has not been exposed to before during neural network training. In the proposed model presented in the study, a CNN is trained to calculate patch antenna phases of PAA using the desired radiation pattern as the input. The proposed CNN model is shown in Fig. 3. The model consists of four convolutional layers and four fully-connected layers, totally eight layers. In the proposed CNN beamforming model, the input is a two-channel radiation pattern that realized gain in both linear and dBi scales, separately. 165,000 samples are used for network training and 40,000 separate samples are used for validation. The training patterns are generated by an 8×8 patch antenna array simulated in ANSYS High Frequency Structure Simulator (HFSS) software. Using the progressive phase shift values for the four sub-arrays, training samples are generated with random beams in the range of $0^{\circ} \leq \theta \leq 45^{\circ}, 0^{\circ} \leq \emptyset \leq 360^{\circ}$. As shown in Fig. 4, the spherical representation (θ, ϕ) of radiation patterns is transformed to the sine-space projection (u, v). Input patterns are scaled to [-1, 1] and normalized to the entire data set. The output phase data, instead of wrapping to [0, 2π] is in the range [-4π, 4π]. Four convolution layers with 10, 20, 30, and 40 filters are used in each layer. The inputs are zero-padded at each layer to maintain a constant output shape number of (45, 46) and all filters have a shape number of (5, 5). To reduce the effects of outliers in the training batch on the weights of each stage, batch normalization is used at each convolution stage. Pooling layers as a critical component of the proposed CNN beamformer are excluded to the model. Pooling layers are important for classification tasks. Pooling layers, in addition to make the convolution spatially and transnationally invariant, making it possible to detect features. For pattern synthesis, the phase output of the NN must be sensitive to spatial location of the desired beam in the input. Therefore, the position of a beam is a critical feature. By removing the pooling layers, the CNN does not benefit from the down-sampling provided by the pooling. As a result, for each convolutional layer with a large number of weights; 82,800 neurons belong to the flattened output of the final convolution layer. As shown in Fig. 3 the output of the convolutional block is divided into four fully-connected parts composed of three hidden layers of 2048, 1024, and 16 neurons, respectively. To reinforce learning for each sub-array, multiple output hidden layer branches are used. At each of the hidden layers, a dropout rate of 30% is applied for reducing over-fitting. The leaky rectified linear unit (ReLU) is used for all layer activations excluding the output. The mean squared error (MSE) function is used for the network. Through the trained network, a radiation pattern is used to verify the performance of the proposed CNN beamformer. As shown in Fig. 3, the desired radiation pattern input to the trained network. The phases are calculated at the output and then, using HFSS to extract the radiation pattern. The NN is able to accurately calculate phases to synthesize the desired pattern if there are minor differences between the two patterns. In [27], using DNN, a linear array antenna with four patch antenna elements is designed. To investigate the effect of DL, large coupling is created between array antenna elements that are spaced 0.28 λ apart (less than half a wavelength). In this research, the radiation pattern with coupling is simulated by directly introducing a signal with a phase difference of 60° to each antenna element. The radiation patterns of the training data are obtained by increasing the phase with 20°changes. In other words, according to angles from zero to 360°, increments of 20° cause 19 modes to appear in each antenna. Therefore, the total number of radiation patterns obtained will be 1 × 19 × 19 × 19 = 6859. Radiation patterns are extracted in units of one degree according to the amount of radiation angle, from zero to 180°. Therefore, the number of input data becomes 181. The initial phase starts at 10°, increases in 40° steps, and stops at 130° (10°, 50°, 90°, and 130°) so; the number of modes created in each antenna will be four and the total number of radiation patterns for model validation will be 1 × 4 ×4 × 4 = 64. The data related to the antenna structure is simulated and stored using a software. The amplitude and phase variables of the antenna are entered into the simulation software and the radiation patterns are extracted. The number of input data was 181 and their values change from zero to one. When the signal phase is set as the output data of the DNN, two different outputs will be generated for the same input due to the equivalence of 0° and 360°. Since this issue may lead to poor learning, the output data of the DNN (amplitude and phase of the array elements) are shown as complex numbers. In this method, 6859 radiation patterns were used to train the model and 64 radiation patterns were used to validate the model. The difference between the proposed method in this research and other conventional methods is that real and imaginary numbers are used to show the phase values in order to increase the ability to learn the desired antenna radiation pattern. Fig. 5 shows the DNN model used in the research. In [28], the pattern synthesis of a PAA is studied using a deep certainty policy gradient algorithm, which is a typical deep reinforcement-learning algorithm and has strong fitting ability for high-dimensional continuous nonlinear problems. Such a feature can be arbitrarily used to design a heterogeneous phased array antenna on the surface of a complex 3D object, which is able to implement fast and complete array radiation pattern guidance. In [29], an array synthesis method with the help of ML based on active base element modeling is proposed. The model proposed in the paper also considers the effects of mutual coupling between each antenna element and the surrounding environment. The result of the study shows that the array synthesis method with the help of ML technique can provide design freedom, array performance, and excellent efficiency. In [30], a DNN is proposed to compute the bone-shaped two-band polarized array antenna at frequencies of 28 GHz and 38 GHz for 5G network applications. In the paper, a DNN model is built on a five-layer system using an adaptive learning algorithm. The framework and hyperparameters of the DNN model, a hybrid algorithm using two particle swarm optimization methods and a modified version of the gravitational search algorithm, are developed. To generate a database for model training and testing, 150 bone-shaped antennas with different geometries in terms of resonance frequency are simulated using a precision DNN model.

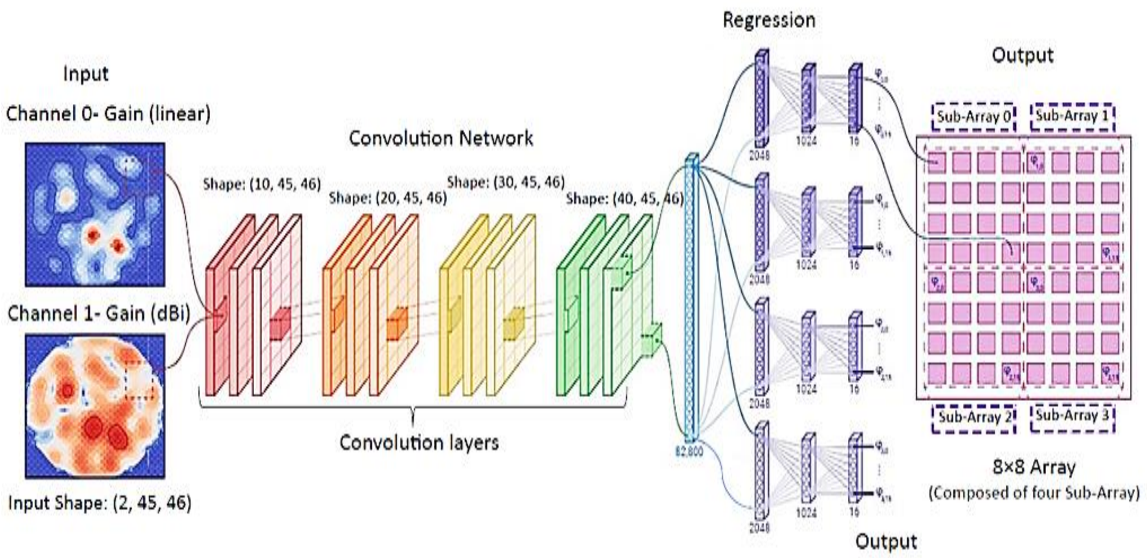


Figure 3. Proposed CNN model in [26]

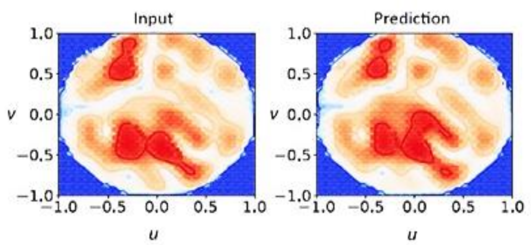


Figure 4. Input and prediction pattern of CNN model proposed in [26]

In [31], an ANN model is proposed to solve the limitation of prior knowledge in ANNs for modeling finite periodic arrays. Considering the problem of mutual coupling in the array, the proposed model in the paper consists of two sub-ANNs: an ANN for elements and an ANN for the array. Based on the relationship between the geometric variables and the electromagnetic behavior of the array elements, NN elements are constructed to provide prior knowledge for array NN modeling. Then, in cross-coupling investigation, the array ANN is modeled to obtain the electromagnetic response of the entire array from the non-linear superposition of the responses of the array elements. In [32], a method for the synthesis of the radiation pattern of almost-periodic arrays that includes the effects of mutual coupling is proposed. In the article, for modeling, the momentum method is combined with the generalized equivalent circuit method and is presented under the name of (MoM-GEC) method. In the article, ANN is used as a computational model in array pattern synthesis. The results of this study show that multilayer direct neural networks can successfully and efficiently provide distinct and complex patterns of quasi-periodic array antennas with sources of different amplitudes. In [33], a phase estimation method between PAA elements based on neural network using linear array radiation power pattern is proposed. To validate the proposed method, the authors apply a radiation pattern measured in a shielded room to the neural network to estimate the initial phase errors and verify the estimation accuracy. The proposed method only requires the measurement of a single radiation pattern for estimation. This shows that the proposed method requires significantly less time compared to other conventional techniques. The research results show that the proposed method is useful for estimating the phase of linear arrays.

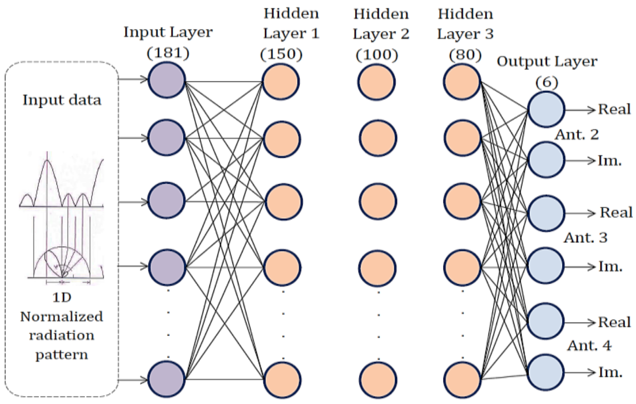


Figure 5. DNN architecture for pattern synthesis of a 4-element linear array (reproduced from reference [50 27])

2) Application of ML in PAA Beamforming, Failure Diagnosis, etc.

In [24], a CNN-based method for array failure detection with support vector machine (SVM) technique is presented. The results of the study show that fault detection in array antennas by DNN is accurate and possible. The accuracy of the proposed DNN method in the research is discussed under different amounts of training data. In [34], considering active PAA for 5G and 6G radios, a DNN for error analysis is proposed. In the paper, DNN is designed to classify various errors by extracting hidden features in phase and components of baseband signals. Validation of the proposed method is performed on a phased array operating at 28 GHz. This method achieves 99% accuracy in detecting the failure of an array element and 80% accuracy for detecting the failure of several array elements. In [35], a cognitive array antenna associated with a deep reinforcement-learning model is proposed for fast adaptation to the complex electromagnetic environment. The platform includes a network analyzer and a programmable control unit to view and adjust the array. The network vector analyzer, through the power divider, supplies the signal to feed the PAA elements and transmits the measured gain to the host computer in order to call the deep reinforcement-learning algorithm. This is done while the programmed control unit controls the digital phase shifters to change the phase of each antenna element when receiving the command to adjust the phase distribution from the deep reinforcement learning model. The result of this research shows a good agreement between the simulated and measured radiation patterns. This algorithm is used to design the PAA and enables automatic adjustment for different beam angles. In [36], a method to obtain the power density value, which provides the standard of human presence exposed to radio frequency electromagnetic field from mobile devices using a DL network. A mobile communication device that uses an array antenna needs a large number of phase conditions to cover a wide communication range. However, the power density values must be calculated repeatedly every time the phase condition changes, which requires a lot of time and cost. To implement this process seamlessly, a DL network is presented in the paper, which can receive the phase conditions of the array antenna and simultaneously provide the power density for the phase conditions of the array antenna as output. In the research, for a 4×1 patch array antenna, which is commonly used in 5G mobile phone communication devices, by changing the phase of the array elements, 5832 radiation patterns are generated as training data and then converted into power density values and the model is trained. The neural network model presented in the research is shown in Fig. 6.

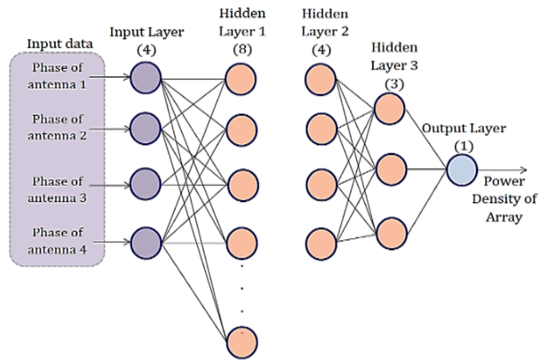


Figure 6. 5-layers NN model to determine the phases of a 4-elements linear array (reproduced from reference [35])

In [37], a DL-based beamformng design approach is proposed, and a beamforming neural network (BFNN) which can be trained to learn how to optimize the beamformer for maximizing the spectral efficiency with hardware limitation and imperfect channel state information (CSI) is presented. Simulation results show that the proposed BFNN achieves significant performance improvement and strong robustness to imperfect CSI over the traditional beamforming algorithms. In [38], a method for generating an adaptive radiation pattern of an array using DL is proposed, which is based on a deep CNN. In this proposal, a radiation pattern is applied as an input to the model, which encodes the desired behavior and calculates the optimal currents required to match the antenna with the desired pattern specifications. This proposal reduces the computation time and provides an intelligent mapping from a classical iteration algorithm to the antenna for its reproduction. After training, the model is able to successfully calculate the optimal flows and avoid costly iterative optimizations to find the required flows (see Fig. 7). Summary of the studies related to the applications of ML in PAAs in the last five years are listed in Table I.

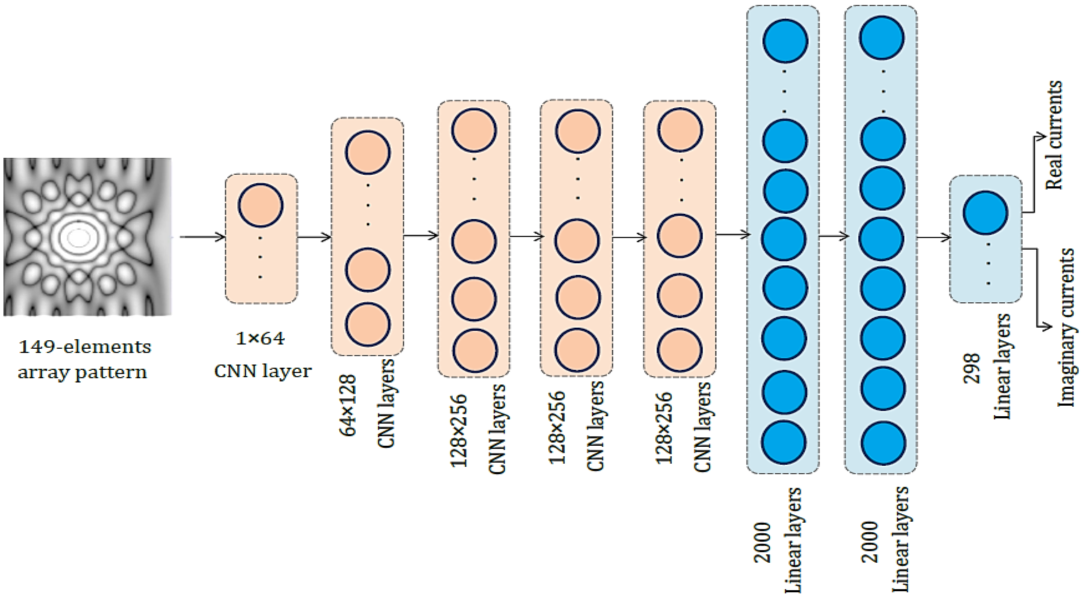


Figure 7. Architecture of the deep CNN for generating an adaptive radiation pattern (reproduced from reference [38])

TABLE I. SUMMARY OF THE STUDIES RELATED TO THE APPLICATIONS OF ML IN PAAS IN THE LAST FIVE YEARS

Ref.	Year	ML Algorithm	Phased Array Type	Application
Shan *et al.* [25]	2018	CNN based on AlexNet	2D Circular aperture reflect array	Synthesis of Reflect array
Chen *et al* [24]	2019	CNN with SVM	2D 5×5 microstrip array at λ/2 interval	antenna array failure diagnosis
Lovato and Gong [26]	2019	CNN	2D 8×8 microstrip patch antenna array	phased antenna array beamforming
Xiao *et al* [31]	2019	ANN	2D array	Design of finite periodic arrays
Bianco *et al.* [38]	2020	CNN	149- elements, λ/2 spaced on a circular aperture array	phase antenna array adaptive beam-forming
Lin and Zhu [37]	2020	DNN	1D 1×64 antenna array at λ/2 interval	Large-scale phase array beamforming
Kim and Choi [27]	2020	5-layers DNN	1D 4×1 array patch antenna	Synthesis of the phased array
Bang and Kim [36]	2021	DNN	1D 4×1 array patch antenna	Power density of phase array
Montaser and Mahmoud [30]	2021	5-layers DNN	Uniform circular antenna array	Circularly polarized bone-shaped patch antenna for 5G
Zhang *et al.* [28]	2022	Deep Deterministic Policy Gradient	1D 1×17 conformal phase array antenna	Conformal PAA pattern synthesis
Iye *et al.* [33]	2022	8-layers NN	1D linear array	Phase estimation method for a linear antenna array
Wu *et al.* [29]	2022	ML assisted array synthesis	1D linear arrays	Synthesis of the phased array under mutual coupling
Nielsen *et al.* [34]	2022	DNN	2D linear arrays	5G and 6G active phased array
Bilel and Taoufik [32]	2022	FFNN	2D planar array	synthesize the pattern of almost periodic arrays
Zhang *et al.* [35]	2022	Deep reinforcement learning	conformal phased array antenna	Cognitive antenna array

B. Research Gaps and Opportunities

In the studies related to the applications of AI especially ML in PAAs, there is a gap regarding adaptive PAA (APAA), which can be an opportunity in future studies in this field. Few studies have been done in relation to the use of ML techniques in APAA. Therefore, it is necessary to conduct more studies in this field. APAA in various areas such as wireless localization, adaptive nulling, multiple input multiple output (MIMO) communication, calibration and failure detection of array elements. APAA is presented with signal processing techniques. these techniques, in addition to use for determining signal parameters such as the direction of arrival (DoA) of the input signal, also used in beam formation and directing it in the desired direction with an approach to minimize interference. Therefore, APAA can be used to perform the following missions: (1) DoA estimation of all input signals (interfering and multipath signals) through DoA algorithms such as Multiple Signal Classification (MUSIC), (2) Signal parameter estimation through rotational invariant techniques (ESPRIT), (3) Distinguish the wanted signal from the unwanted input signals, (4) In addition to direct and track the radiation pattern in the direction of the desired signal, place it in the DOA of the interfering and multipath null pattern signals [39].

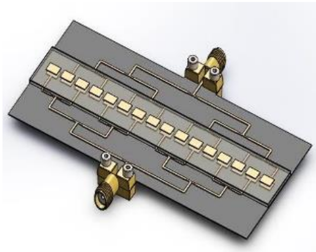
These capabilities are achieved using adaptive algorithms such as least mean square (LMS) and recursive least squares (RLS) through dynamic updates of phase weights in array elements. The main item of APAA systems is the digital signal processor (DSP). DSP can calculate the complex weights by managing the received data information and multiply the weights in each antenna element. In addition to optimizing the radiation pattern of the array, this operation also causes the radiation pattern to be shaped to minimize the interference [40, 41]. In APAA, in conventional methods, some algorithms such as Auxiliary Sources method is used to find the optimal antenna for a given pattern [42]. In traditional methods, for obtaining an optimal antenna with a periodically changing directional pattern numerical experiments are performed [43, 44]. In particular, AI-based methods can perform much more powerfully in noisy and multi-path environments compared to conventional algorithms in digital signal processing. Therefore, using ML techniques in APAA systems can be an opportunity in future studies to improve the application of APAAs in various communication systems.

III. Phased Array Antenna (PAA)

PAA is a multi-antenna package whose desirable radiation pattern is conducted in a certain direction while suppressing undesirable radiations. In addition, to change the direction of the PAA radiation, there is no need to move the antenna mechanically, and the direction of the pattern is electronically controlled. These capabilities cause the PAA to find many applications in communication systems. By PAA, it is possible to achieve more reliable and robust telecommunication links by reducing the “multi-path fading” and “co-channel interference” problems due to suppression of unwanted signals emitted from other directions. PAAs are used in “base stations” of mobile cellular networks to increase the coverage of the main signal in a desired area while suppressing interference in the other areas [15 45]. Satellite television (TV) systems also use PAA. PAA-based broadcast links have higher performance in adverse weather, being smaller and lighter in weight, which can be easily installed on the walls and roofs compared to traditional parabolic dish systems. In addition, the adaptive shaping of the radiation pattern in such antennas allows moving objects such as airplanes to access satellite programs [46]. In addition to telecommunication applications, biomedical applications can benefit from the advantages of PAAs [47–49]. For example, in microwave imaging to detect breast cancer PAAs are used [50–52].

A. PAA Structure

Antenna radiation pattern or simply antenna pattern is defined as a mathematical function or a graphical representation of antenna radiation properties. In most cases, the antenna pattern is obtained in the antenna far field [53]. The elements of a PAA can be arranged linearly (one dimension), planarly (two dimensions), or conformal (three dimensions) to produce different radiation patterns. Fig. 8 shows linear and planar array antennas.



(a)

(b)

Figure 8. PAA types, a) linear [54], b) planar [55].

In array antennas that consist of a number of similar elements, the antenna pattern is obtained based on the theorem of pattern multiplication [56]:

$$\textit{Array radiation pattern} = \textit{Array element radiation pattern} \times \textit{Array factor (AF)} \qquad (1)$$

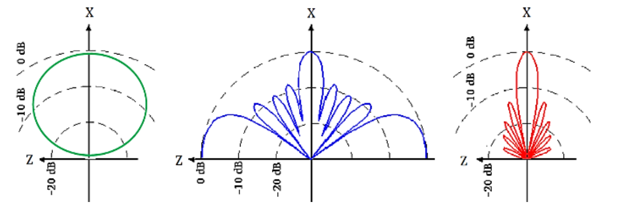
Fig. 9 depicts the array pattern obtained by multiplying the array element pattern by the *AF* for a 5-elements array (array elements are horn antennas). In the pattern multiplication theorem, AF is a function that depends on the geometry of the array and excitation currents of the elements in terms of their phase and feeding range. Therefore, AF depends on the array type. Fig. 10 shows a simple schematic of linear and planar arrays. It is assumed that the array elements are located at equal distances (d).

1) AF in linear array

Assuming that all array elements are identical, the AF is independent of the array element type. Therefore, the field of an array element with radiation angle θ located at the origin is obtained from the following equation:

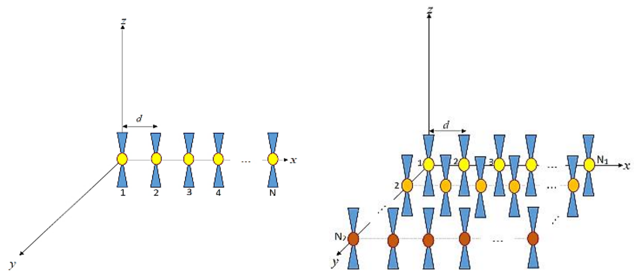
$$E_\theta = I_0 \frac{e^{-jkr}}{4\pi r} \quad (2)$$

where, I_0 is the excitation current of the isotropic element, k is the free space wave number, and r is the distance of the observation point from the origin. It is assumed that all elements are located at the same distance d from each other. The concepts of r, d, and θ for a linear array with eight elements are shown in Fig. 11.



(a) (b) (c)

Figure 9. Radiation pattern of a 5-elemens linear array composed of five $1\lambda \times 1\lambda$ horn antenna: a) a horn antenna pattern, b) AF, c) array pattern [57]



(a) (b)

Figure 10. Schematic of PAA: a) linear array with N-elements, b) planar array with $N_1 \times N_2$-elements

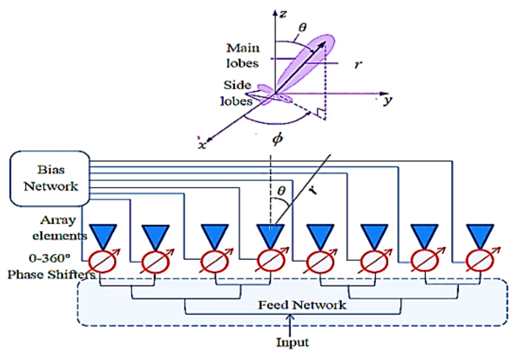


Figure 11. A linear array with eight elements.

It is assumed that the excitation current of the elements are equal and the element located at the origin is considered as the reference phase (i.e., $\emptyset_1 = 0$).

$$I_1 = I_0, \quad I_2 = I_0 e^{j\emptyset_2}, \ldots, \quad I_N = I_0 e^{j\emptyset_N} \quad (3)$$

The electromagnetic fields around the elements are obtained as follows:

$$E_{\theta_1} \approx I_0 \frac{e^{-jkr}}{4\pi r} = E_0 \quad (4)$$

$$E_{\theta_2} \approx I_0 e^{j\emptyset_2} \frac{e^{-jk(r-dcos\theta)}}{4\pi r} = E_0 e^{j(\emptyset_2 + kdcos\theta)} \quad (5)$$

$$E_{\theta_N} \approx I_0 e^{j\emptyset_N} \frac{e^{-jk[r-(N-1)dcos\theta]}}{4\pi r} = E_0 e^{j[\emptyset_N + (N-1)kdcos\theta]} \quad (6)$$

The array field is obtained from the superposition of the array element fields and is expressed as follows:

$$E_\theta = E_{\theta_1} + E_{\theta_2} + \cdots + E_{\theta_N} = E_0 \times AF \quad (7)$$

The AF for a linear array with N elements separated by d is obtained by Eq. (5) as follows:

$$AF = [1 + e^{j(\emptyset_2 + kdcos\theta)} + \cdots + e^{j[\emptyset_N + (N-1)kdcos\theta}] \quad (8)$$

The phases of uniform linear array elements (with the same elements and the same distances) with the linear phase progressing from one element to another are as follows:

$$\emptyset_1 = 0, \ \ \emptyset_2 = \alpha, \ \ \emptyset_3 = 2\alpha, \ldots, \emptyset_N = (N-1)\alpha \quad (9)$$

where, α is the amount of phase change of array elements. By inserting the linear phase values in the general formula of an array with N elements, AF is obtained as follows:

$$AF = \left[1 + e^{j(\alpha + kdcos\theta)} + \cdots + e^{j(N-1)[\alpha + kdcos\theta}\right] = \sum_{n=1}^{N} e^{j(n-1)\psi} \quad (10)$$

The term α+$kdcos\theta$ which is denoted by ψ is array function phase, which is related to the distance of elements, phase shifts, and radiation angles. If the AF in Eq. (6) is multiplied by $e^{j\psi}$, the following relation is resulted:

$$AF \times e^{j\psi} = [e^{j\psi} + e^{2j\psi} + \cdots + e^{jN\psi}] \quad (11)$$

By subtracting the AF from the above equation, AF can be obtained as follows:

$$AF = e^{J(n-1)\frac{\psi}{2}} \frac{\sin\left(\frac{N\psi}{2}\right)}{\sin\left(\frac{\psi}{2}\right)} \quad (12)$$

The exponential in Eq. (10) shows the phase shift of the phase center of the array relative to the origin. If the position of the array is moved so that the center of the array is at the origin, the phase term is lost and finally, the AF after phase change and normalization becomes the following simple form:

$$AF = \frac{1}{N} \frac{\sin\left(\frac{N\psi}{2}\right)}{\sin\left(\frac{\psi}{2}\right)} \quad (13)$$

PAA usually consist of a feeding network and phase shifters. The feeding network and the phase shifters are used to control the phase of element currents to obtain the pattern of the array antenna for radiation in the desired direction [58] perform distribution of the transmitter signal (current) to the elements. In general, the array-feeding networks can be divided into three main classes: (1) limited feeding, (2) spatial feeding, and (3) semi-limited feeding (a combination of limited and spatial feeding) [59]. In a spatial feeding, the array is fed by a separate feeding horn located at a suitable distance from the array [60]. Fixed feed, which is the simplest method, power is taken from a source and through a feed line is distributed to the elements. The limited feeding method is classified into two main types: (1) parallel feeding, and (2) serial feeding [61]. As an example, the parallel feeding method in a linear array with eight elements is shown in Fig. 11.

2) AF in planar array

Unlike linear array, which can only scan the original radiation pattern of the array in one polar plane (elevation or azimuth plane), planar array can scan the original pattern in both θ and ϕ directions. Compared to linear arrays, planar arrays have higher gain and fewer sub-lobes. The principles of planar array design are similar to the linear array. In planar array, the elements are arranged in two dimensions, and AF can be shown as the product of the AF of two linear arrays, one along the *x*-axis and the other along the *y*-axis (Fig. 10 (b)) [62]:

$$AF = AF_x \times AF_y = \frac{\sin(\frac{N_1\psi_x}{2})\sin(\frac{N_2\psi_y}{2})}{N_1\sin(\frac{\psi_x}{2})N_2\sin(\frac{\psi_y}{2})} \quad (14)$$

$$\psi_x = kd_x sin\theta cos\phi + \alpha_x \quad (15)$$

$$\psi_y = kd_y sin\theta cos\phi + \alpha_y \quad (16)$$

3) AF in conformal array

When the array elements are arranged properly in a space, they can form three-dimensional (3D) or conformal array. In this case, the AF is shown as follows:

$$AF = AF_x \times AF_y \times AF_z = \frac{\sin(\frac{N_1\psi_x}{2})\sin(\frac{N_2\psi_y}{2})sin(\frac{N_3\psi_z}{2})}{N_1\sin(\frac{\psi_x}{2})N_2\sin(\frac{\psi_y}{2})N_3\sin(\frac{\psi_z}{2})} \quad (17)$$

$$\psi_x = kd_x sin\theta cos\phi + \alpha_x \quad (18)$$

$$\psi_y = kd_y sin\theta cos\phi + \alpha_y \quad (19)$$

$$\psi_z = kd_z cos\theta + \alpha_z \quad (20)$$

IV. ML TECHNIQUES AND ALGORITHMS

ML can give computers the ability to learn without explicit programming. ML is a branch of computer science in which machines are designed so that can program themselves [63]. The training process is simply learning from previous experiences or observations, such as guidelines for looking for patterns in data so that the better decision can be made by the machine. The main goal of ML is learned automatically and do tasks without human intervention [64, 65]. Fig. 12 illustrates ML process. Previous data is used to train the model and then the trained model is used to test new data, and finally to predict the results. Trained model performance is evaluated by a part of the previously available data (data not provided during model training). This is called the model validation process. It measures the accuracy of the model's performance on data that has not been seen by the model before. In this case, the ratio of the number of correctly predicted features to the total features available for prediction describes the accuracy of the model.

ML techniques can be classified into four general classes including: (1) supervised, (2) unsupervised, (3) semi-supervised, and (4) reinforcement learning. Algorithms have been proposed for each of these techniques.

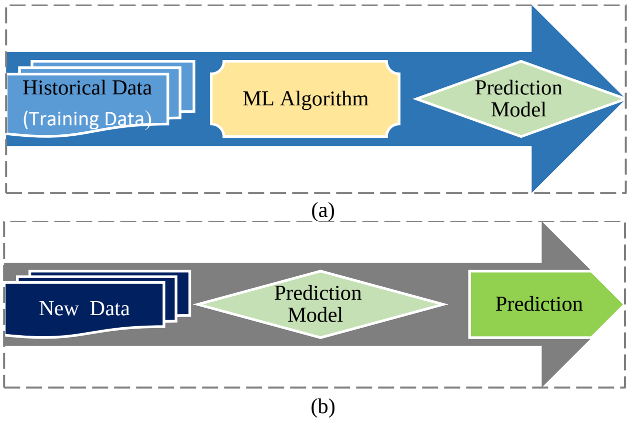


Figure 12. ML process: a) model training, b) model evaluation.

A. ML techniques

1) Supervised learning

In supervised learning new data is derived using labeled data based on what they have already learned and to predict future events or labels. In this technique, monitoring which means labeling the data is used to guide or modify the model. For this purpose, the training set is known and then the learning algorithm predicts the output. By comparing the predicted output with the actual output and if errors are identified, the model can be corrected while correcting them [63].

2) Unsupervised learning

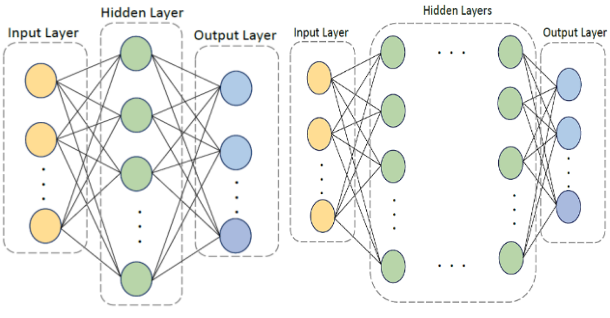
In these types of techniques, there is no observer (label) to guide or correct the model. These types of ML techniques are used when there is unlabeled or unclassified data to train the model. In this case, the system does not correctly define the output, but explores the data in such a way that it can extract rules from the data set and describe the hidden structures of the unlabeled data [63-65].

3) Semi-Supervised learning

These techniques are methods that fall between supervised and unsupervised learning. Therefore, these types of learning algorithms use both unlabeled and labeled data for training purposes. In general, they use less labeled data and more unlabeled data. This technique is used to improve the accuracy of learning.

4) *Reinforcement learning*

These techniques are a type of learning method that is rewarded or punished based on the work done by the system. If the system is trained to do a certain task but does not do it, the system can be punished. However, if the system performs well, it will be rewarded. This is represented as 0 and 1, where 0 represents punishment and 1 represents reward.



(a) (b)

Figure 13. Comparison of ANN and DNN: a) ANN, b) DNN

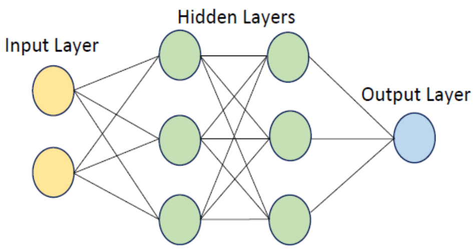


Figure 14. FNN structure with two hidden layers.

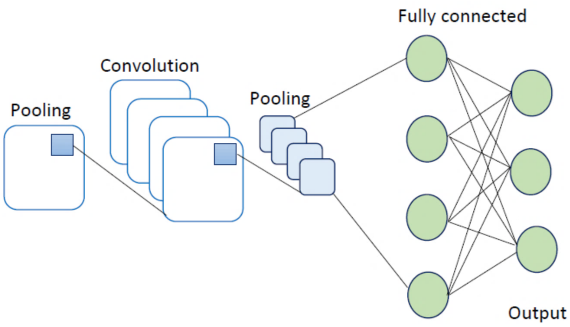


Figure 15. CNN structure.

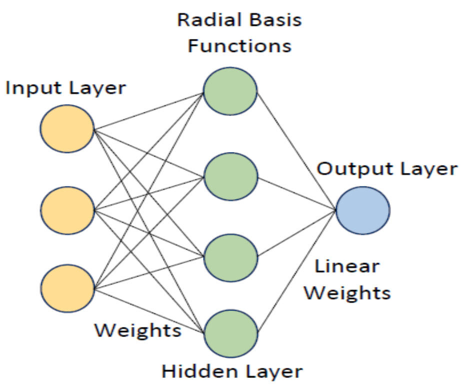


Figure 16. RBFNN structure.

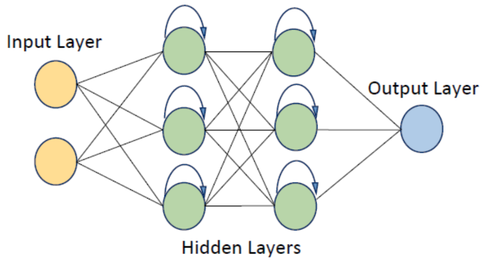


Figure 17. RNN structure with two hidden layers.

B. *ML Algorithms*

Different methods are used to categorize ML algorithms. One of them is classification based on similarities. In this article, we have categorized ML algorithms based on the similarity of their performance. Although this method of categorization may be useful, it is not perfect. Because there are still algorithms that can easily fall into different categories, such as vector quantization training, which is both a neural network-inspired method and a sample-based method. The ML algorithms can be grouped according to their similarities [66].

Among the ML algorithms, ANN algorithms are models that are inspired by the structure or function of biological neural networks. These algorithms are a class of pattern matching that are commonly used for regression and classification problems, but are actually a huge sub-field of hundreds of different algorithms used to solve variousproblems. The main difference between ANN and deep neural network (DNN) is in the number of their hidden layers. In other words, there is only one hidden layer in the ANN, while DNN has more than one hidden layer. Fig. 13 shows the general schemes of ANN and DNN. In ANN, we deal with methods that are more classical. DL algorithms are a modern update to ANNs that exploit abundant low-cost computations. DL algorithms build much larger and more complex neural networks, and many DL methods are associated with very large labeled datasets. In general, DNNs consist of simple processing interconnected nodes and three types of layers. These layers are: 1) the input layer, which contains the feed data, 2) the hidden layer/layers, which are responsible for all the calculations, and 3) the output layer, which produces the result. We mention some of the most popular NNs in this section as follow [67]:

- FNN: Feedforward NN or simply FNN is the simplest type of NN, and as can be seen from Fig. 14, this type of NN consists of several simple neurons organized in layers. Each unit in a layer is connected to all units in the previous, while there are not any feedback connections on the model outputs.
- CNN: Convolutional NN or simply CNN is a remarkable class of NNs in which they use convolution instead of multiplicative neurons (see Fig. 15). For example, the generation of image features is done by applying a filter on the image, as it can use the correlation between pixels. Such NNs are popular for classification tasks and for obtaining spatial features of the input layer.
- RBFNN: In radial basis function NN or simply RBFNN, a type of function is used which changes

according to the distance from a location and acts as activation function. As shown in Fig. 16, RBFNN consists of input, hidden layers, and an output. Depending on the basis function and the number of hidden layers, RBFNN can be considered non-linear.

- RNN: Recurrent NN or simply RNN differs from FNN in having a feedback loop and exploiting previous input data to influence subsequent inputs due to its memory (see Fig. 17). As a result, they are mainly used for temporal tasks. Due to their key impact in various research fields, two advanced RNN architectures are discussed, namely long short-term memory (LSTM) and gated recurrent unit (GRU).

V. Conclusion

One of the most widely used antennas in communication systems are PAAs, which have attracted the attention of researchers due to the development of their applications. An important issue in the design of PAAs is the synthesis of their radiation patterns. Since in a PAA, the desired radiation pattern is obtained by adjusting the phase difference between signals feeding the array elements, therefore, providing a model to obtain the desired radiation pattern is an important and fundamental issue in the design of these antennas. In conventional PAA synthesis methods, use antenna simulation software that is based on electromagnetic models. These models are very time-consuming in addition to having errors. Recently, ML techniques have been used to design and synthesize array antennas. By replacing ML techniques instead of electromagnetic simulation, in addition to increasing accuracy and reducing errors in PAA pattern synthesis, the design process time is also reduced and time is saved. In this paper, we reviewed the ML techniques in PAA synthesis. This study shows that the use of ML techniques leads to the improvement of PAA synthesis in communication systems. There are a few challenges related to ML applications, such as feature engineering, existence of the hyper parameters, capacity, complexity, and the necessity of conducting multiple experiments for a suitable architecture. The large number of parameters and meta-parameters required for tuning is the main weakness of ML techniques, which makes the process complicated and time-consuming. Nevertheless, it can be hoped that ML techniques will play a dominant role in the design of array antennas through faster solutions. The key advantage of ML techniques is the accuracy in solving complex problems. The main opportunities ahead regarding the application of ML techniques in PAAs are: (a) improving the level of evolution of ML techniques in order to achieve better results with understanding of the structure and continuous training, and (b) achieving a balance between precision and accuracy of complexity in order to quickly demonstrate its general superiority over traditional approaches. Furthermore, the implementation of a real-time platform to evaluate the actual speed-up factors is needed, which is subject to ongoing and future studies. In addition, in the studies related to the applications of AI especially ML in PAA, there is a gap regarding adaptive PAA (APAA), which can be an opportunity in future studies in this field. Therefore, the use of ML techniques in the design of APAA can be an opportunity to improve the methods of using APAAs in various applications.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Mohammad Reza Ghaderi contributed to the machine learning algorithms development for the article, as well as the initial paper writing. Nasrin Amiri contributed to phased array antenna synthesis methods and fine-tuning the manuscript. All research activities were conducted under the supervision of Mohammad Reza Ghaderi. All authors have approved the final version of the paper.

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